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Original Article

An Enhanced Distributed Energy-Efficient Clustering Protocol with Improved Weighed Quantum Particle Swarm Optimization for Dynamic Cluster Allocation and Coordinated Transmission in WSN to Improve Performance Measures

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Abstract *- This paper introduces an enhanced Distributed Energy-Efficient Clustering (DEEC) protocol combined with Improved Weighed Quantum Particle Swarm Optimization (IWQPSO) to address critical issues in Wireless Sensor Networks (WSNs), such as limited energy resources, uneven energy distribution, dynamic network conditions, and communication overhead. WSNs are vital for data collection and transmission in various applications, but their efficiency is hindered by these challenges. The proposed method leverages DEEC-IWQPSO for dynamic cluster allocation, optimizing the selection of CHs and cluster formations based on real-time network conditions like traffic load and resource availability. The integration of quantum principles in IWQPSO enhances the exploration and convergence speed of the optimization process, leading to more efficient resource utilization and energy management. The primary objectives are to improve energy efficiency, extend network lifetime, optimize data transmission, minimize communication overhead, and ensure scalability in large WSN environments. Simulation results demonstrate that the proposed DEEC-IWQPSO protocol reduces energy consumption by up to 35%, increases network lifetime by 30%, improves data transmission reliability by 25%, and reduces communication overhead by 20% compared to existing methods. These outcomes highlight the protocol's ability to provide a scalable and energy-efficient solution for WSNs, making it suitable for diverse, resource-constrained environments.*

Keywords *- Wireless Sensor Networks, Distributed Energy-Efficient Clustering, Improved Weighed Quantum Particle Swarm Optimization, Dynamic cluster allocation, Energy efficiency, Network lifetime, Coordinated transmission, Data transmission efficiency, Resource optimization, Quantum optimization.*

1. Introduction

The sensor nodes use microprocessors to process the information they acquire and then send or receive the processed data to or from nearby nodes in the wireless sensor network. In a centralized sensor network, all sensing nodes are connected to each other and to a centralized control node known as the SINK through the network [1]. The SINK gathers information requested by the consumer from the network's nodes. The SINK is designed with broadcasting capabilities, allowing it to trigger network sensors by transmitting control and policy data for various applications [2]. Figure 1 provides a graphical overview of a WSN. It gained popularity over the past decade due to its ability to evaluate, automate, and manage applications that improve living conditions. WSN consists of several small computers called sensor nodes. WSN is primarily used for activity sensing and monitoring of fields, machinery, environments, etc [3]. The creation, execution, and operation of a sensor network require careful consideration of signal processing, communication protocols, data handling, etc. Compared to existing application-specific sensor networks, WSNs in IoT contexts have a larger coverage area and a higher number of sensor nodes [4]. More advanced energy-efficient routing techniques are required than the existing ones designed for WSNs with relatively modest coverage areas. To overcome these challenges, the scalability and cost-effectiveness of WSNs are crucial in all design aspects, including secure key management, network architecture, and routing protocols [5].

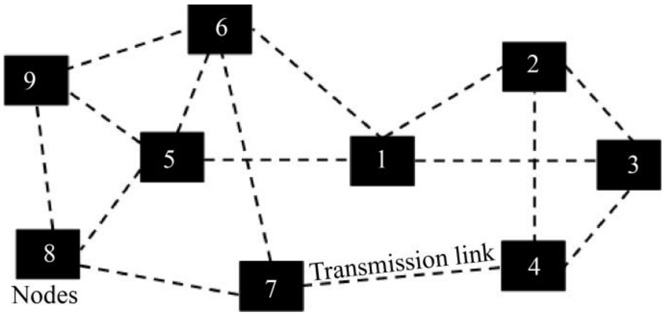


Fig. 1 Graphical representation of wireless sensor network

Routing protocols can be classified into two categories based on node deployment: hierarchical (cluster-based) routing and flat routing. In flat routing protocols, every sensor node performs the same function, transmitting data from sensors to the base station. For example, in LEACH, one-hop communication involves the Cluster Head (CH) gathering data from its member nodes and sending it directly to the Base Station (BS) [6]. Single-hop protocols are advantageous due to their low cost and latency, and if the network covers a small area, every node in the field can reach the entire sensor field with its communication range. Researchers used the variable k as a sub-optimized fixed value for small-area sensor networks [7]. k needs to be optimized for large-area WSNs with more sensor nodes. Decentralized cluster-based routing systems use control messages to manage message transmission, join requests, CH advertisements, and other operations [8]. In the LEACH method and most of its variations, nodes transmit control messages with maximum power to reach the entire network, ensuring that even the farthest nodes in the sensor field receive the signals [9].

These internet-connected, wirelessly deployed smart sensor nodes offer unprecedented possibilities for various military and civilian applications, such as industrial process control, environmental monitoring, and battlefield surveillance [10]. The initial driving force behind the development of WSNs was military use, particularly for battlefield monitoring. WSNs are now employed in a wide range of civilian applications such as traffic management, home automation, healthcare, and environmental and habitat monitoring [11]. The deployment of small cells, including Remote Radio Heads (RRH), picocells for outdoor street coverage, and femtocells for personal indoor access, has significantly increased the number of access points.

This type of deployment deviates from the existing regulated cellular design by placing points of contact in a pseudo-regular pattern and relying on known propagation or penetration models [12]. Recently, the Random Network (RN) topology, where BSs and Mobile Stations (MSs) are randomly distributed throughout space, has been developed to simulate this new model. It is important to note that the Poisson Point Process (PPP), widely used for its statistical tractability, cannot adequately represent real-world deployments of commercial services. As a result, important insights into the performance of dense cellular networks can be obtained [13].

For example, the mathematical calculation of coverage in an RN considers both general and specific cases of fading. Research shows that PPP distributions provide a lower bound on the efficiency of existing cellular networks and can be viewed as a worst-case deployment scenario [14]. Multiple tiers of randomly placed base stations in Heterogeneous Networks (HetNets) with different transmission powers can be modeled as a single RN architecture. The tightly packed, unplanned nature of dense cellular networks makes existing frequency planning for optimal utilization of costly spectrum resources difficult [15]. In this research, Coordinated Multiple-Point (CoMP) transmission is considered a key technology for future dense cellular networks, as it is an efficient approach to reduce inter-cell interference (ICI). Interference becomes a much greater issue than in existing cellular networks [16].

1.1. Problem Statement

Wireless Sensor Networks (WSNs) are widely used for real-time monitoring and data collection in diverse environments. However, their performance is critically constrained by limited energy resources and inefficient communication strategies. Existing static clustering techniques often result in unbalanced energy consumption among nodes, leading to premature node failures and reduced network lifetime. Moreover, the lack of intelligent coordination in data transmission contributes to increased latency, redundant communication, and reduced throughput. Dynamic cluster allocation, if not optimized, can further lead to frequent reclustering overhead and instability. Therefore, there is a pressing need for an adaptive and energy-aware clustering mechanism coupled with coordinated transmission that can dynamically form optimal clusters, select energy-efficient cluster heads, and reduce communication costs. Addressing these challenges is essential for enhancing key performance measures such as energy efficiency, network longevity, data delivery rate, and overall reliability of WSNs.

1.2. Motivation

The growing deployment of Wireless Sensor Networks (WSNs) in critical applications such as environmental monitoring, military surveillance, and smart agriculture demands highly efficient and robust communication protocols. One of the primary challenges in WSNs is the limited energy capacity of sensor nodes, which directly impacts the network's operational lifetime and data reliability. Static clustering and existing routing techniques often fall short in addressing energy imbalances and adapting to dynamic network conditions. This motivates the development of intelligent, adaptive clustering mechanisms that can dynamically adjust to node energy levels and network topology changes. Incorporating metaheuristic optimization, such as Improved Weighed Quantum Particle Swarm

Optimization (IWQPSO), offers a promising solution to optimize cluster formation and data transmission paths. The aim is to maximize energy efficiency, ensure balanced load distribution, and enhance overall network performance. This research is driven by the need to overcome existing protocols' limitations and design a scalable, energy-aware framework for efficient data aggregation and coordinated transmission in WSNs.

1.3. Research Gap

Despite the extensive research on clustering and energy-efficient communication protocols in Wireless Sensor Networks (WSNs), several critical gaps remain unaddressed. Most existing protocols, such as LEACH, DEEC, and SEP, rely on static or semi-dynamic clustering approaches that do not fully exploit real-time network conditions, leading to uneven energy depletion and reduced network stability. Additionally, current optimization-based methods often struggle with premature convergence, a lack of exploration-exploitation balance, and suboptimal cluster head selection in dense or large-scale deployments.

Few studies effectively integrate dynamic cluster allocation with coordinated transmission strategies to reduce redundant data forwarding and ensure optimal load balancing. Furthermore, the potential of hybrid metaheuristic algorithms like Improved Weighed Quantum Particle Swarm Optimization (IWQPSO) remains underexplored for dynamic and distributed WSN environments. Therefore, there is a clear need for a robust, adaptive framework that addresses these limitations by combining intelligent optimization with real-time coordination to significantly improve energy efficiency, data delivery, and network lifetime in WSNs.

2. Related Works

Fixed spectrum allocation laws mitigate interference between various wireless systems by separating the frequencies at which they operate. This fixed allocation strategy has contributed to the spectrum shortage. Recent studies have shown that several parts of the allocated spectrum are significantly underused [17]. Additional users can only operate in licensed frequency ranges if they do not interfere with Primary Radios (PRs) operations. Cognitive Radios (CRs) aim to address this issue by providing Opportunistic Spectrum Access (OSA) through advanced technology [18]. Two types of previously proposed Control Channel Allocation (CCA) systems for Cognitive Radio Networks (CRNs) can be distinguished: (a) dynamic distribution, which is based on factors such as geographical correlation, spectrum usage, and connection degree, and (b) static assignment of a specialized band of frequencies shared by all CRs [19].

Several studies have proposed an always-available static band of frequencies, known to all nodes, for sharing control information. The CORVUS system, which utilizes UWB technology for managing traffic, was proposed. Using ISM bands for control in CRNs presented an OFDM-based approach that enables control messages to be transmitted over long distances with low bit error rates [20]. In this method, the spectrum accessible to the maximum number of one-hop neighbors is selected as a control band, dividing the CRN into groups. This approach reduces the management overhead by minimizing the number of unique frequency bands required for control. Due to variations in PR activity, frequent reclustering may occur [21].

A different cluster-based architecture was introduced, a swarm intelligence-based technique for adjusting control channels in response to interference readings. Nearby CRs negotiate with one another to select a control channel, but PRs are not considered during these negotiations [22]. Proposed dynamic channel hopping based on pseudo-random patterns, where transmitter-receiver pairs periodically hop through different frequency bands, selecting shared rendezvous channels to communicate until the information exchange is complete. One drawback of this approach is that it does not account for potential PR interference during these hops [23].

Dynamic Control Channel Allocation Schemes introduced WhiteFi, a technology that enables WiFi-like communication over UHF white spaces. WhiteFi uses dynamic channel assignment techniques to identify and manage available frequencies. WhiteFi utilizes one primary control channel and one backup control channel to manage in-band control traffic [24].

The positions of these channels change according to spectrum dynamics. The SOC system clusters the CRN into regions where multiple idle channels can be used for control traffic, making it more resilient to spectrum changes over time [25].

In cluster-based systems, mobile nodes are grouped into virtual clusters. Each cluster maintains proximity to other clusters, with the same regulations applying to every group. A cluster may consist of members, group pathways, and a CH node. Cluster gateways facilitate inter-cluster data transfer [26]. Clustering techniques for sensor networks can be classified based on several factors. Monitoring hop frequency between node pairs within a cluster is another way to differentiate various cluster-based designs. Multilevel topologies with random changes require high communication overheads to maintain the hierarchical structure [27].

In contrast, single-level clustering only monitors changes in the local structure caused by host mobility and has simpler CH management [28]. Provides another classification of clustering procedures based on different objectives. The six clustering approaches include load-balancing grouping, environmentally friendly grouping, mobility-aware clustering, easy-to-maintain grouping, Dominating-Set-based (DS-based) clustering and combined-metrics-based clustering [29].

3. Materials and Methods

3.1. Problem Formulation

Dynamic Cluster Allocation and Coordinated Transmission in WSN to improve performance measures. Given that sensor nodes have limited energy resources, one of the primary goals is to optimize network performance measures such as energy efficiency, network lifetime, and data transmission reliability. Achieving these goals requires an efficient mechanism for dynamic cluster allocation and coordinated transmission. The objective is to minimize overall energy consumption while maximizing data transmission efficiency and network lifetime by dynamically adjusting cluster formations and managing CH selection based on network conditions.

3.2. Mathematical Formulation

3.2.1. Energy Consumption Model

A network can be broken down into energy for transmission, reception, and data aggregation. Let E_{total} represent the total energy consumption.

$$E_{ti}(k,d) = E_{elec}.k + E_{amp}.k.d^{\gamma} \quad (1)$$

Where: K = number of bits to transmit; E_{elec} Energy required per bit for processing (electronics); E_{amp} energy required by the transmission amplifier; d = distance between the transmitting node and receiving node (either CH or BS); γ = path loss exponent (typically 2 for free space, 4 for multipath fading)

The energy for receiving a packet of size k is given by:

$$E_{ri}(k) = E_{elec}.k \quad (2)$$

The energy used for data aggregation by the CH is:

$$E_{DA}(K) = E_{DA}.K \quad (3)$$

Where E_{DA} Represents the energy required for data aggregation.

The total energy consumed by a node during one communication round is:

$$E_{total} = E_{ri}(k,d) + E_{ri}(k) + E_{DA}(K) \quad (4)$$

3.2.2. CH Selection Model

It is crucial for reducing energy consumption and balancing the load across nodes. Introduce a binary decision variable. i_x, where $i_x = 1$ if node x is selected as a CH and $i_x = 0$ otherwise.

$$min \sum_{x=1}^{N} E_{total}\,(x) \quad (5)$$

$$\text{Subject to: } \sum_{x=1}^{N} i_x = p.N \quad (6)$$

Where: N = total number of sensor nodes; p = desired fraction of nodes to be CHs in a given round.

3.2.3. Dynamic Cluster Formation

To form clusters dynamically, define the communication cost for each sensor node based on its distance to the nearest CH. The energy cost for node x to transmit data to its CH is proportional to $d_{x,CH}$. The total communication cost C for the network is:

$$C = \sum_{x=1}^{N} E_{ti}(k, d_{x,CH}) \quad (7)$$

The goal is to minimize the communication cost expressed as:

$$minC = min \sum_{x=1}^{N} d_{x,CH}^{\gamma} \quad (8)$$

3.2.4. Coordinated Transmission Model

$$T_{CH} = \frac{L}{R} \quad (9)$$

Where: L size of the data packet; R = transmission rate of the CH

The goal is to minimize the total transmission delay while ensuring reliable data delivery. This is done by balancing the load across CHs and avoiding overloading any single cluster.

3.2.5. Objective Function

The overall objective of the dynamic cluster allocation and coordinated transmission problem is to minimize energy consumption, communication cost, and transmission delay while maximizing network lifetime. This can be formulated as a multi-objective optimization problem:

$$\min(E_{total}, C, T_{CH}) \quad (10)$$

subject to:

1. Energy constraints of sensor nodes.
2. CH selection and dynamic cluster formation constraints.
3. Real-time adaptation to network conditions.

In WSN, the issue of coordinated transmissions and dynamic cluster assignment is defined to enhance important performance metrics, such as transmission dependability, environmental sustainability, and network longevity. In energy-constrained contexts, this approach guarantees the ability to grow and the long-term viability of WSNs through the integration of dynamic clustering and optimization of transmission techniques. Figure 2 depicts the CCA issue that this research addresses. When a CR detects an idle cellular channel nearby, it will opportunistically exploit that channel. Intend to provide CRs the freedom to decide on a CCA based on the vacancies in their spectrum. As a result, distinct channels need to be designated for management in various communities. The CRN naturally separates several clusters as a result of this assignment, each of which has at least one shared idle channel.

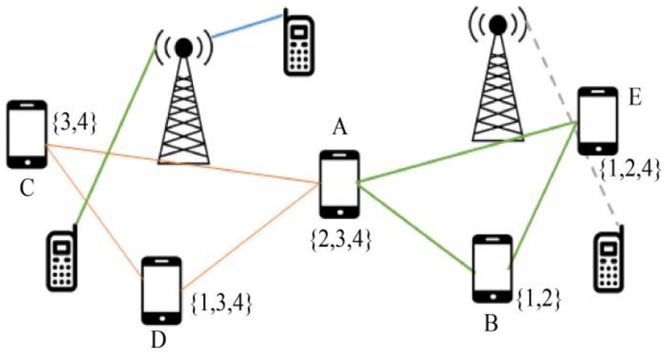


Fig. 2 CCA based on PR activity

3.3. Enhanced DEEC Protocol

One popular protocol for heterogeneous WSNs that is efficient in terms of energy is DEEC. CH's decision is made by a probability function. This function combines the network's typical electricity consumption and residual power. Every cluster node's probability function is calculated. All WSN nodes are expected to start with varying amounts of energy, newly added or energy-harvested networks with a greater power reserve than older ones. A subset of these nodes is designated as CHs, and it is their responsibility to provide the combined data to the BS.

Advanced nodes and regular nodes are the two categories into which the sensor nodes are divided. High-energy nodes constitute advanced nodes. E_0 is the starting power of normal nodes, and m is the proportion of advanced nodes. As much energy is contained in advanced nodes at one time as in typical nodes. Thus, the overall amount of advanced nodes in WSN is $Nm,$ and the amount of electricity linked to these networks is $E_0(1+a)$. On the other hand, there are $N(1-m)$ total normal nodes and E_0 It is the quantity of energy connected with these nodes. As a result, the total amount of energy is multiplied by $(1+am)$ times.

$$E_{total} = N(1-m)E_0 + NmE_0(1+a) = NE_0(1+am) \quad (11)$$

Every node on the internet does not have the same amount of leftover energy as it develops. Consequently, the epoch and the probability of LEACH do not function well for heterogeneous networks, as shown in Figure 3. Assume that Si (i = 1, 2, 3, 4,... N) nodes are distributed over the sensor field. Every node in every round has an expectation function attached to it that determines whether or not that node gets elected as CH. Let be the number of rotations that a node S_i must complete to become the rotating epoch ensemble head. According to LEACH, low-energy nodes will perish rapidly if the value varies for every node, since each node has a unique energy consumption associated with it. Depending on the remaining energy or Ei(r), DEEC employs several methods. Equation (12) may be used to determine the median chance Piof a node being a CH during rounds.

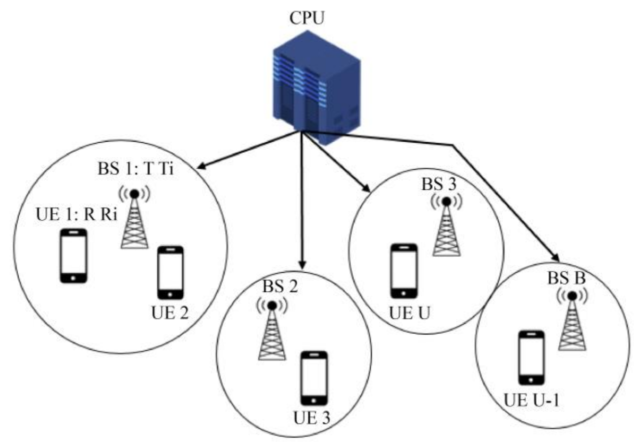


Fig. 3 The large-scale clustered MIMO-aided network

$$P_x = \frac{1}{n_x} \quad (12)$$

Equation (13) is used to calculate the median power of the entire network.

$$\bar{E}(r) = \frac{1}{N}\sum_{x=1}^{N} E_x(r) \quad (13)$$

Equation (14) is used to define the likelihood of the xth node using average energy as the reference energy. Sensor nodes in heterogeneous networks dynamically determine probabilities while considering starting and remaining energy. The remaining energy, the averaged energy and predetermined P_{opt} Make up election likelihood.

$$P_x = P_{opt}\left[1 - \frac{\bar{E}(r) - E_x(r)}{\bar{E}(r)}\right] = P_{opt}\frac{E_x(r)}{\bar{E}(r)} \quad (14)$$

$$\sum_{\boldsymbol{x=1}}^{\boldsymbol{N}} P_x = \sum_{\boldsymbol{x=1}}^{\boldsymbol{N}} P_{opt}\frac{E_x(r)}{\bar{E}(r)} = P_{opt}\sum_{\boldsymbol{x=1}}^{\boldsymbol{N}}\frac{E_x(r)}{\bar{E}(r)} = P_{opt}N \quad (15)$$

Equation (15) establishes the median number of CH for each epoch. The residual and standard energy (E(r) is regarded as the reference energy) determine how many CH are produced.

Every node in DEEC shares data about the overall energy consumption and network longevity, as shown in Figure 4. Equation (16) computes the total energy (E_{total}) and average energy $(\overline{E}(r))$ of the network to get the mean probability (P_x). The BS provides the lifespan value (R). Equation (17) is used to get the mean power of the network in rounds.

$$\bar{E}(r) = \frac{1}{N}E_{total}\left(1 - \frac{r}{R}\right) \quad (16)$$

$$R = \frac{E_{total}}{E_{round}} \quad (17)$$

Radio transmission of l-bit message and distance (d) is computed by using Equation (18).

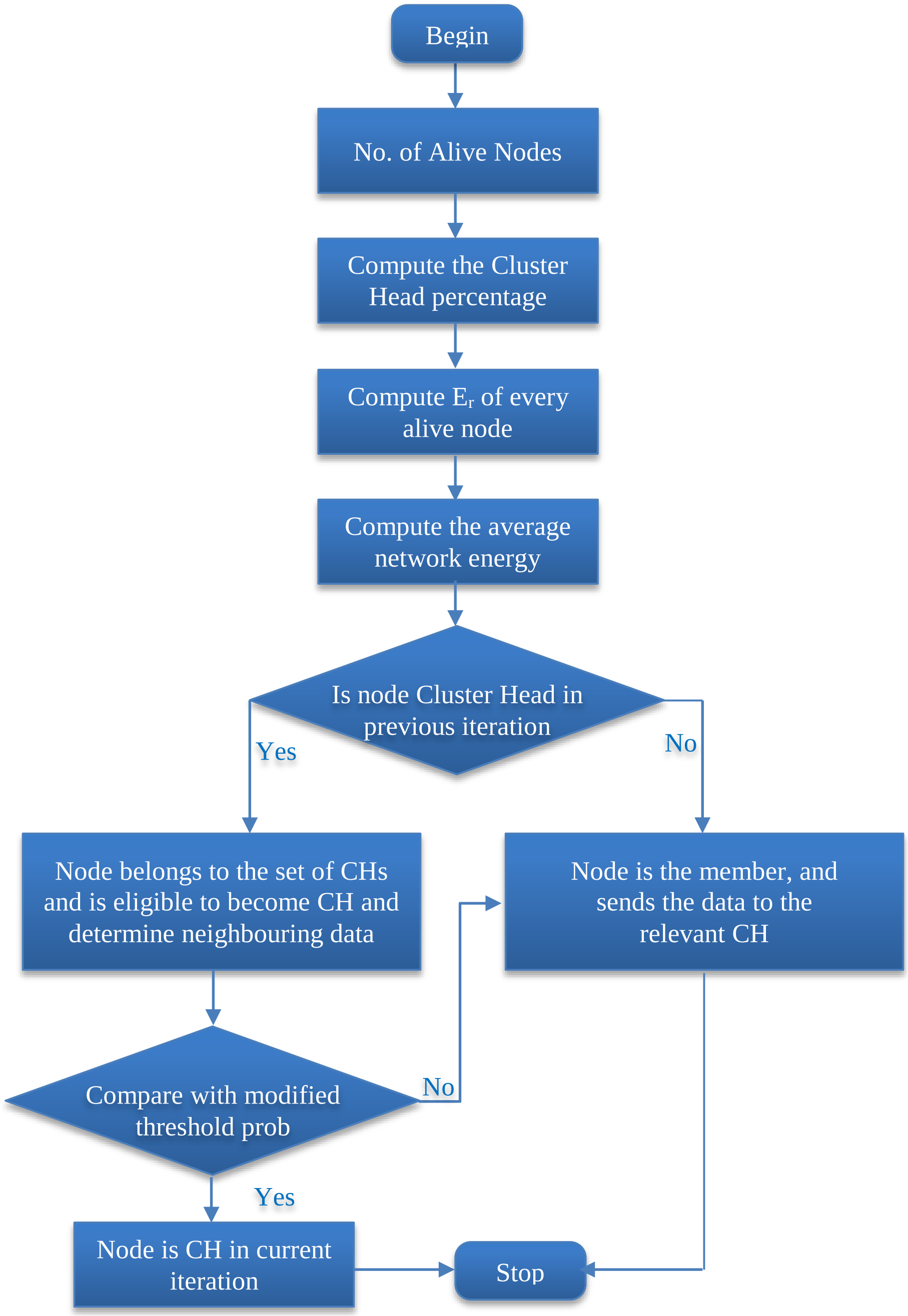


Fig. 4 Flow chart of the proposed enhanced DEEC algorithm

$$E_{Ti}(1,d) = \begin{cases} 1E_{elec} + 1\epsilon_{fs}d^2, & d < d_0 \\ 1E_{elec} + 1\epsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (18)$$

$$E_{round} = L\left(2NE_{elec} + NE_{DA} + k\epsilon_{mp}d^4_{CHtoBS} + N\epsilon_{mp}d^2_{NtoCH}\right) \quad (19)$$

3.4. Improved Weighed Quantum PSO

A group of people with random answers or atoms is used for the initialization of IWQPSO. Every answer was given a random position and velocity inside the searching space's dth dimension. The aim of IWQPSO is to find the particle's placement that yields the best assessment of the specified fitness function. All of the pbest values aggregated to provide an overall approach are produced while the particle group works toward improvement. After comparing each pbest value, the particle with the closest and most optimized outcomes is designated as the worldwide best particle, or gbest. The search space is allocated to every particle in the first two examples (g_{best} and p_{best}), and every particle has moved inside that search space. Suppose the particles are given locations as indicated in Figure 5, and each particle is given a local area. In that case, these local values will be compared to obtain the optimal solution known as l_{best}.

IWQPSO has been effectively used in various research and application fields over the past several years since it has been discovered to produce faster and less expensive findings than other approaches. There are only a few parameters that vary little and function effectively in numerous IWQPSO applications.

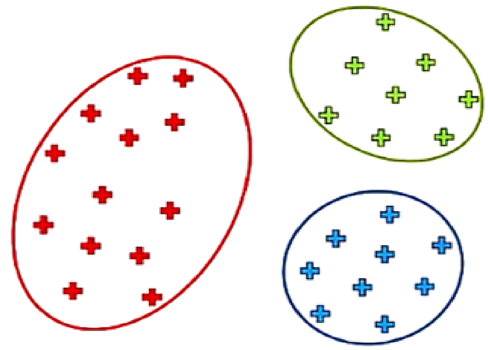


Fig. 5 Search space in topological order

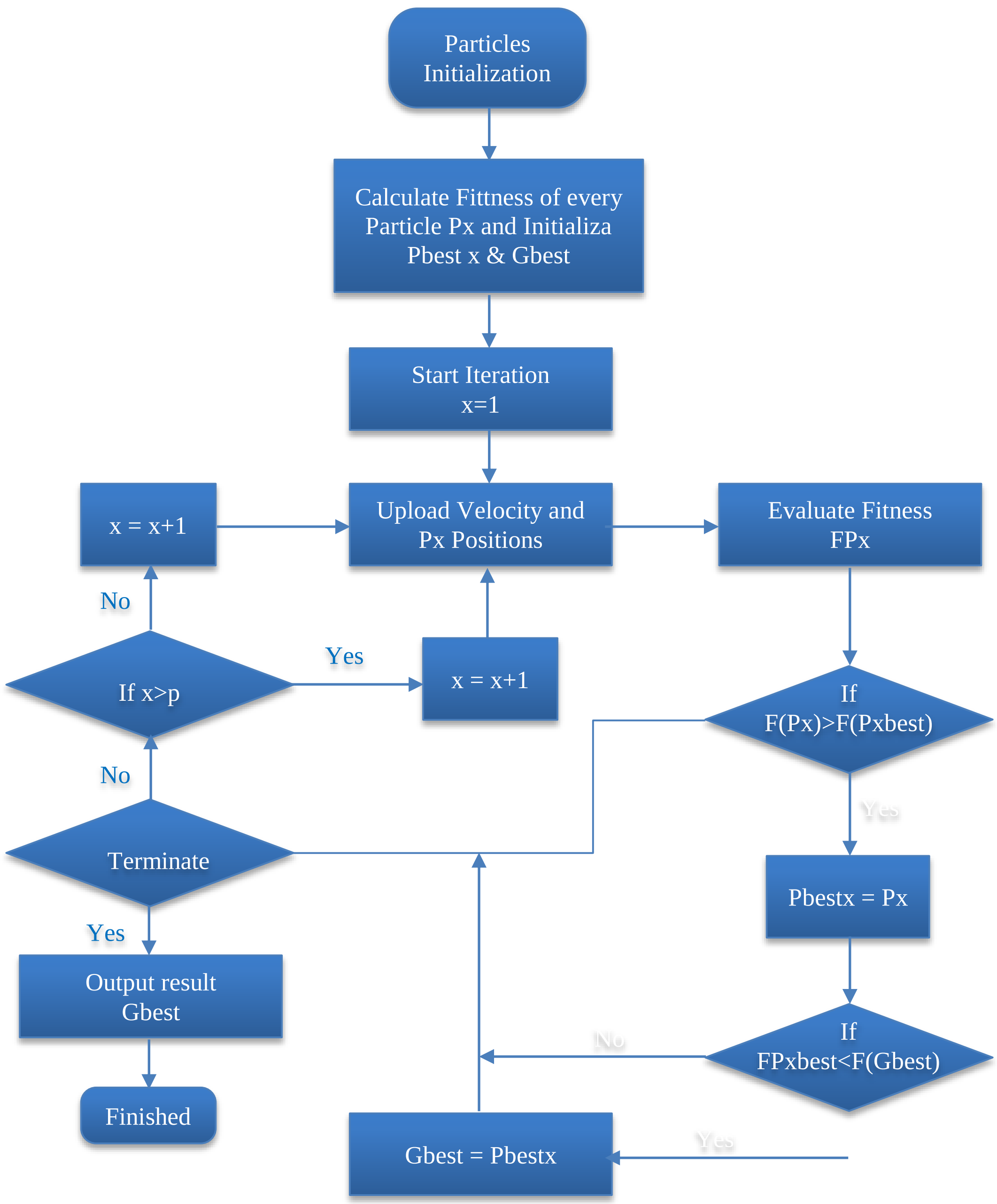


Fig. 6 Flowchart for the IWQPSO algorithm

Sensor nodes are distributed at random throughout the sensor field. The network under consideration is homogeneous, meaning that each sensor node's starting energy is the same. Following random implementation, sensor nodes remain immobile. The position of the BS is also set. After deployment, replacement of batteries or recharge is not possible due to energy constraints on sensor nodes. For sensor nodes, the clustering hierarchy is taken into account. Data is sent via sensor nodes to the CH, where it is aggregated and then sent to the sink. For an effective energy dissipation model, open space and multipath fading channels must be taken into account. Equation (20) is used to calculate the energy usage for sending M bits across a distance d.

$$E_{Ti}(M,d)=\begin{cases}M.E_{elec}+M.\epsilon_{fs}d^2, & d<d_0\\ M.E_{elec}+M.\epsilon_{mp}d^4, & d\geq d_0\end{cases} \quad (20)$$

The swarm's particles adjust their positions in response to the group's position and velocity. The motion of particles is determined by two factors: particle-to-particle and iteration-to-iteration. Particle motion causes the best place visited by a particle as a whole to be recorded as g_{best}, while iteration causes individuals to keep their favorite spot as best. The several PSO actions are explained by the flowchart in Figure 6. Particle P_x In the quest for the universe, it has location and speed in the dth dimension. The following notation is used to express the population's xth particle. P_x

$$P_x=\left[I_{x,1},I_{x,2},\ldots,I_{x,D}\right] \quad (21)$$

$$V_{new,x}=w*V_x+c_1*r_1*(Ipbest_x-I_x)+c_2*r_2*(Ig_{best}-I_x) \quad (22)$$

$$I_{new,x}=I_{old,x}+V_{new,x} \quad (23)$$

3.5. Objective Function for Dynamic Cluster Allocation and Coordinated Transmission in WSN

The objective function for dynamic cluster allocation and coordinated transmission in WSNs aims to optimize multiple performance metrics, primarily focusing on minimizing energy consumption, communication cost, and transmission delay while maximizing the network lifetime.

$$minf(i)=\alpha_1E_{total}(i)+\alpha_2C(i)+\alpha_3T_{CH}(i)+\alpha_2 \quad (23)$$

Where: f(i) = Objective function to be minimized. $E_{total}(i)$ = Total energy consumption as a function of cluster allocation and transmission decisions. $C(i)$ = Total communication cost associated with cluster formations and transmission.

$T_{CH}(i)$ = Total transmission delay from CHs to the base station. $\alpha_1,\alpha_2,\alpha_3$ = Weights assigned to each objective, reflecting their importance in the optimization process. (These weights should sum up to 1, i.e., $\alpha_1+\alpha_2+\alpha_3=1$).

3.5.1. Total Energy Consumption $E_{total}(i)$

$$E_{total}(i)=\sum_{x=1}^{N}\left(E_{ti}\left(k,d_{x,CH}\right)+E_{ri}(k)+E_{DA}(k)\right).i_x \quad (24)$$

Where i_x It is a binary decision variable indicating whether node x is a CH or not.

3.5.2. Total Communication Cost C(i)

$$C(i)=\sum_{x=1}^{N}E_{ti}\left(k,d_{x,CH}\right).i_x \quad (25)$$

This cost measures the energy required to communicate between node x and its associated CH.

3.5.3. Total Transmission Delay $T_{CH}(i)$

$$T_{CH}(i)=\sum_{y=1}^{M}\frac{L_y}{R_y}.j_y \quad (26)$$

$$d_{x,CH}\leq d_{max} \quad (27)$$

Where M is the total number of CHs, L_y Is the size of the data packet from CH y? R_y Is the transmission rate of CHy, and j_y It is a binary decision variable indicating whether CH y is transmitting or not.

The objective function effectively captures the trade-offs between energy consumption, communication cost, and transmission delay while optimizing dynamic cluster allocation and coordinated transmission in WSNs. By adjusting the weights $\alpha_1,\alpha_2, and\alpha_3$The optimization can be tailored to focus on the most critical performance measures based on specific application requirements.

Algorithm: DEEC- IWQPSO

This algorithm aims to improve energy efficiency in WSNs by leveraging a DEEC protocol with an enhanced optimization technique, IWQPSO. The proposed algorithm dynamically allocates CHs, optimizes resource distribution, and balances energy consumption, ultimately improving overall network performance.

Algorithm Steps

Step 1: Initialization

Network Initialization: Define the number of sensor nodes N, energy parameters for each node (initial energy $E_{0,x}$), and maximum rounds R_{max}. Set the transmission radius. r_T, total energy E_{total}, and energy threshold for each node.

PSO Parameters: Number of particles P. Maximum iterations $X_{\max}$

Initialize particle positions $I_{\text{x}}(t)$ (possible CH locations) and velocities $V_{\text{x}}(t)$ randomly.

Set the cognitive and social coefficients C_1, C_2, and inertia weight w.

$I_x(t) = [i_{x1}, i_{x2}, \dots, i_{xN}], V_x(t) = [v_{x1}, v_{x2}, \dots, v_{xN}]$,
Objective Function: Minimize the total energy consumption $E_{total.}$ Maximize the network lifetime L.

Step 2: Fitness Evaluation

CH Selection Criteria: Calculate the energy cost for each particle E_x in terms of the distance between nodes and selected CHs.

$$E_x(I) = \sum_{y=1}^{N} \left(E_{Ti} + E_{Amp}.d_{y,CH}^2\right) \tag{28}$$

Where $d_{y,CH}$Is the distance between node y and its CH? E_{Tr} Is the energy consumed during transmission, and E_{Amp} is the amplifier energy.

Fitness Function: The fitness function is based on energy consumption, cluster stability, and transmission efficiency:

$$f(I_x) - \alpha_1 E_{total}(I_x) + \alpha_2(\frac{1}{L(I_x)}) + \alpha_3 C(I_x) \tag{29}$$

Where: $E_{total}(I_x)$ is the total energy consumed by the particle. $L(I_x)$ Is the network lifetime. $C(I_x)$represents the communication overhead.

Step 3: Update Velocity and Position (PSO)

Velocity Update: Update the velocity for each particle using the PSO formula with weighted quantum effects for better exploration:

$$V_x(t+1) = w.V_x(t) + c_1.r_1.\left(P_{best,x}, I_x(t)\right) + c_2.r_2(G_{best}.I_x(t)) \tag{30}$$

Where: $P_{best,x}$ It is the best personal position for particle i. G_{best} Is the global best position found by the entire swarm? r_1,r_2 are random values between 0 and 1.

Quantum Update: Apply a quantum behavior to enhance convergence and avoid local optima:

$$I_x(t+1) = I_x(t) + \frac{h}{m}.sin(V_x(t+1)) \tag{31}$$

Where h is the reduced Planck constant and m is the mass of the particle.

Position Update: Update the particle's position based on its new velocity:

$$I_x(t+1) = I_x(t) + V_x(t+1) \tag{32}$$

Step 4: Dynamic Cluster Formation

Cluster Formation: Based on the updated particle positions, clusters are formed by assigning each node to the nearest CH.

$$C_y = arg \min_x d(y, CH_x) \tag{33}$$

Where $d(y, CH_x)$ is the distance between node y and CH x.

Energy Evaluation for CHs: Evaluate the remaining energy for each selected CH and adjust if a node's energy is below a predefined threshold.

$$E_{remaining}(CH_x) = E_{initial}(CH_x) - E_{used}(CH_x) \tag{34}$$

Step 5: Coordinated Transmission and Energy Consumption

Transmission Model: For each CH CH_x Aggregate data and transmit it to the BS.

$$E_{Ti} = L.E_{elec} + L.E_{amp}.d_{CH-BS}^2 \tag{35}$$

Where L is the data packet size, E_{elec} Is the energy spent on electronics, and E_{amp} Is the amplifier energy coefficient.

Coordinated Transmission: Minimize the communication cost by reducing redundant transmissions and optimizing transmission paths within the network.

Step 6: Termination Criteria

Stopping Condition: The algorithm stops if:

- Maximum number of iterations X_{max} is reached.
- The improvement in fitness between iterations is smaller than a predefined threshold ϵ.

Step 7: Output

Optimized CHs: The algorithm outputs the final CH selection and its corresponding cluster members.

Performance Metrics: Energy efficiency, network lifetime, and communication cost are used to evaluate the protocol's performance.

The proposed DEEC Protocol with IWQPSO optimizes dynamic cluster allocation and coordinated transmission in WSNs. By reducing energy consumption and improving network lifetime, this method offers a significant improvement in the overall performance of WSN.

4. Results and Discussions

To evaluate the effectiveness of the proposed Enhanced Distributed Energy-Efficient Clustering Protocol (E-DEECP) integrated with Improved Weighed Quantum Particle Swarm Optimization (IWQPSO), simulations were conducted using MATLAB R2023a. A wireless sensor network (WSN) comprising 100 sensor nodes was randomly deployed over a 100 m × 100 m area. Each node was equipped with limited initial energy and static position assumptions, with the base station located either centrally or outside the monitored field to simulate real-world deployment scenarios. The network model followed a first-order radio energy consumption model for data transmission and reception. The IWQPSO was applied dynamically for optimal cluster head selection and adaptive cluster formation in each round, aiming to minimize intra-cluster distance and energy consumption while maximizing network lifetime and throughput. Performance metrics such as network lifetime, stability period, residual energy, number of alive nodes, and end-to-end delay were evaluated over 500 simulation rounds. The proposed approach was benchmarked against classical protocols like LEACH, SEP, and DEEC to validate its superior energy efficiency and scalability. All nodes are thought to be stationary. BS is presumed to be positioned in the middle of the network field. Figure 7 displays the distribution of dead nodes in the sensor field. Network Lifetime is based on dead nodes, as shown in Table 1.

Table 1. Network Lifetime based on dead nodes for the proposed and LEACH methods

Method	Iterations count		
	1st Node Die (rounds)	50% of nodes die (rounds)	Last Node Die (rounds)
LEACH	1110	1275	1580
DEEC-IWQPSO	1160	1350	3890 (10 alive nodes)

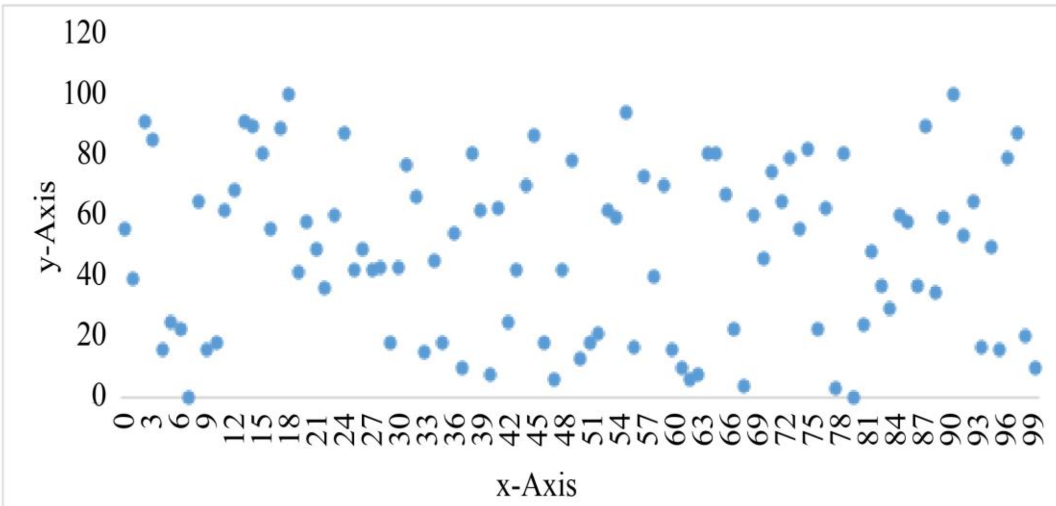


Fig. 7 Sensor field used for experiment

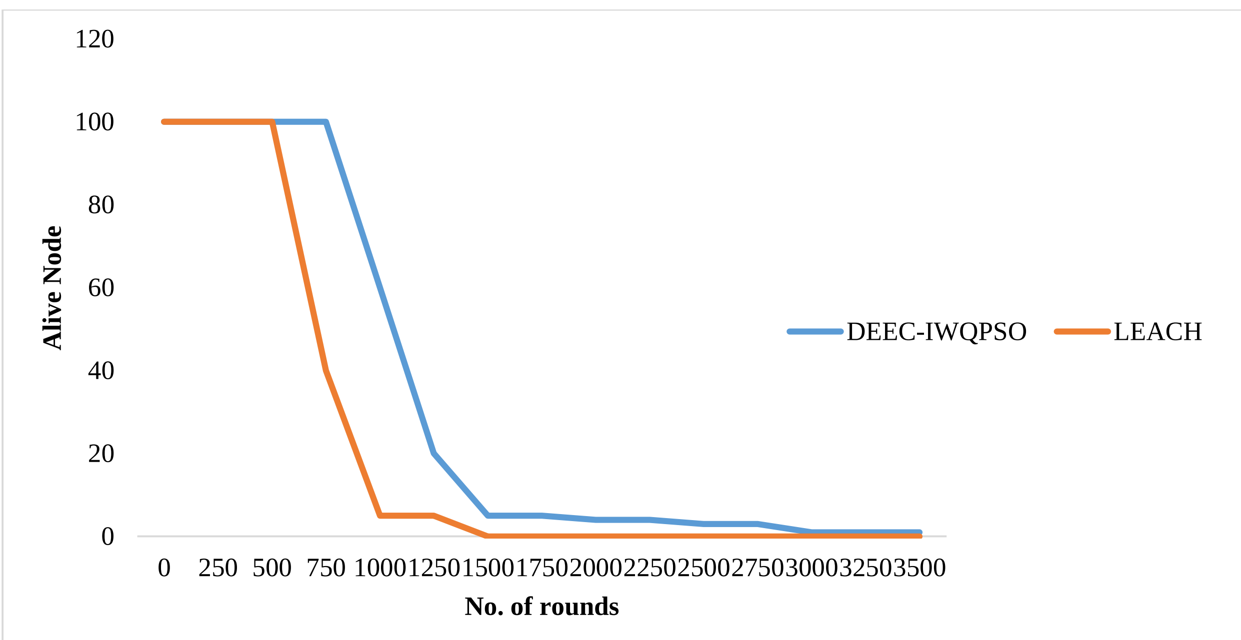


Fig. 8 Comparison of live nodes of all rounds

Comparison of live and dead nodes (every round) for the proposed and LEACH methods is displayed in Figures 8 and 9.

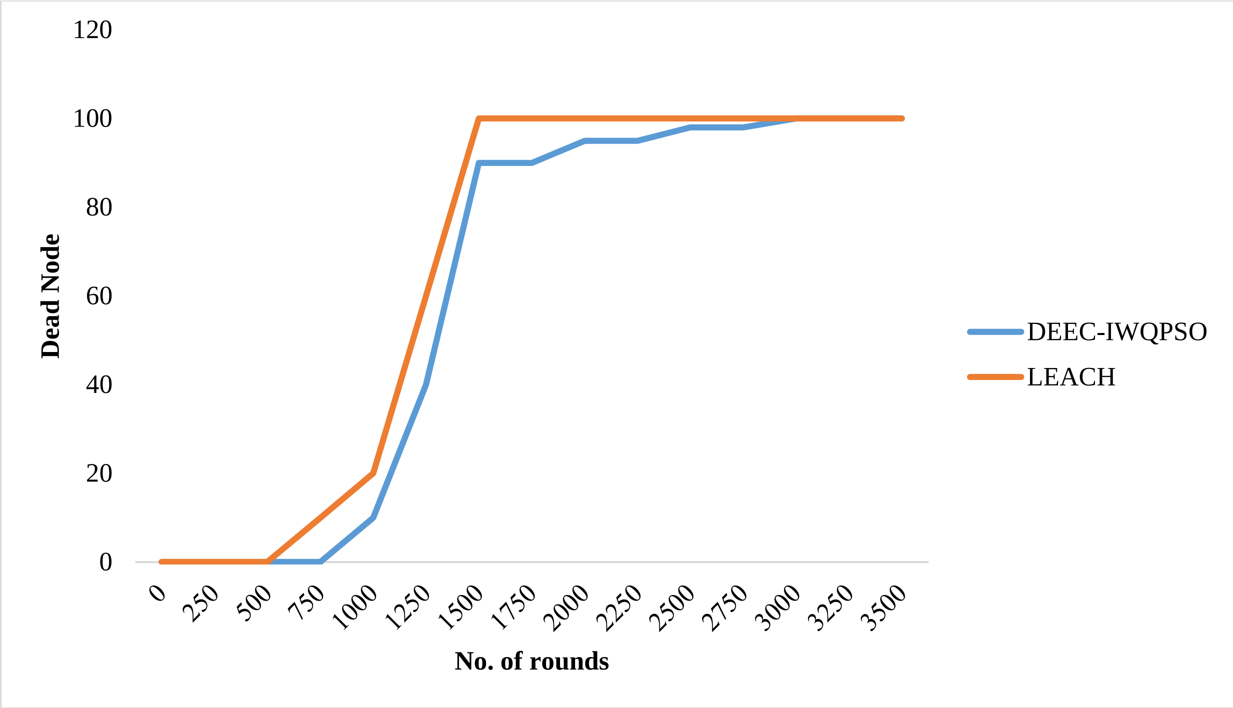
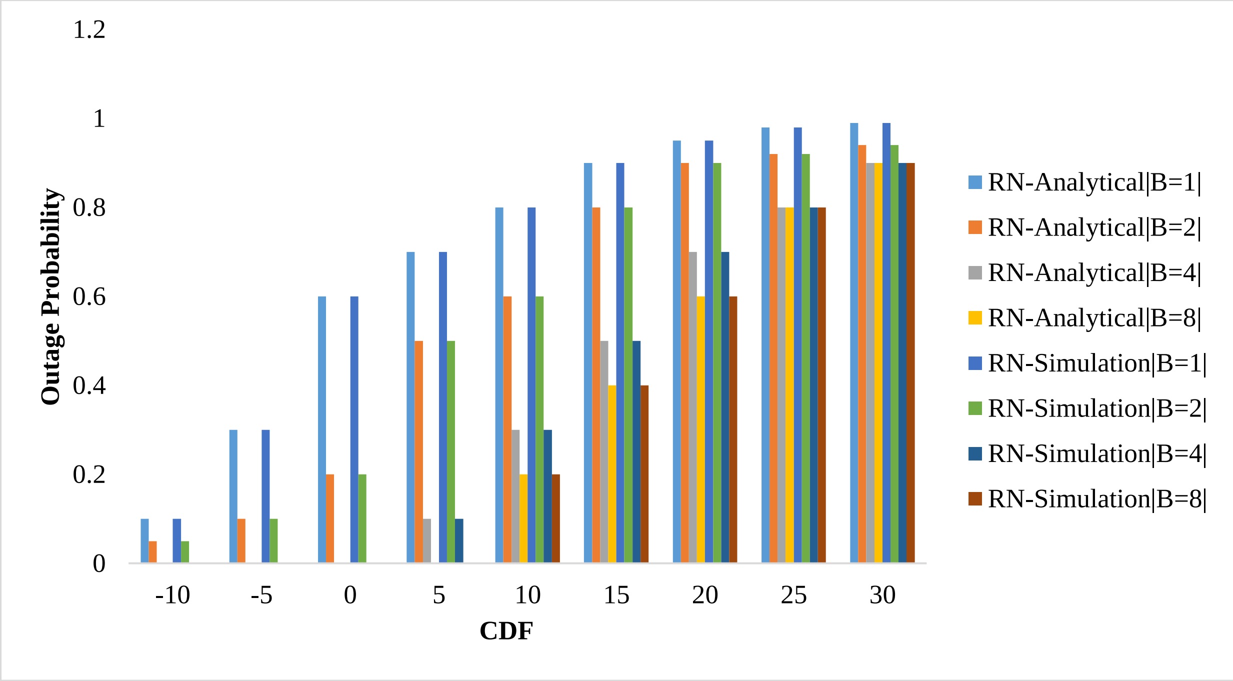
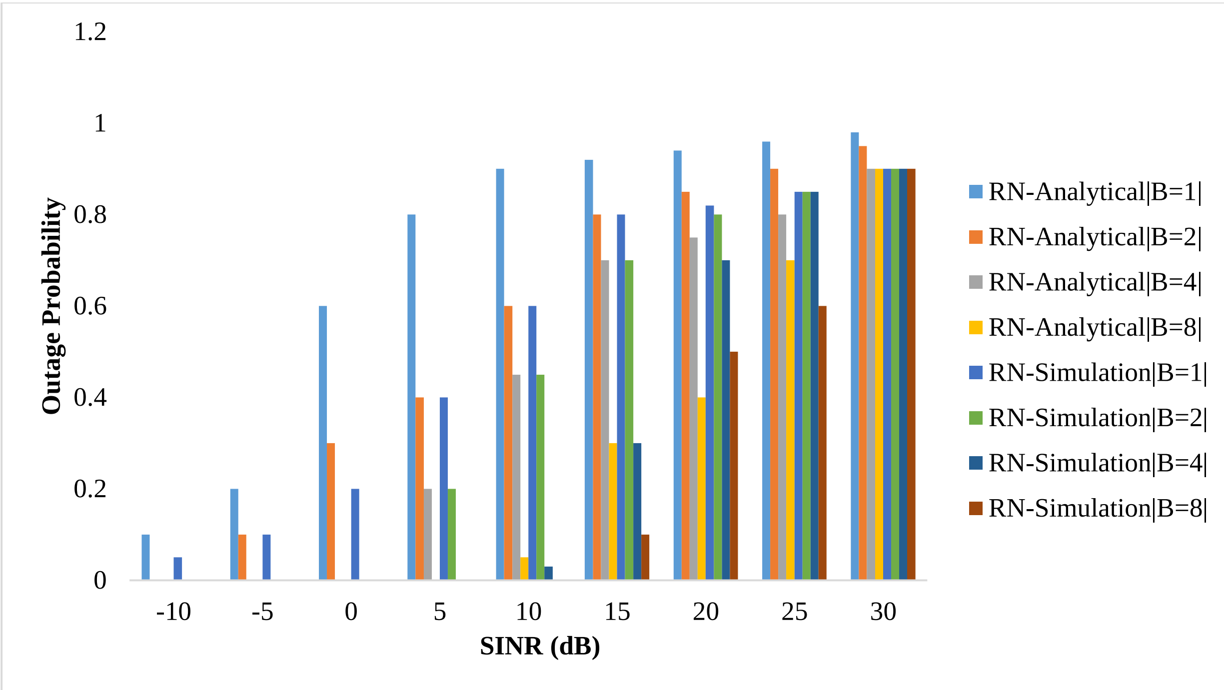


Fig. 9 Comparison of dead nodes of all rounds

First, the internet CDF outage probability derived from the assessment and simulation for the RN architecture is plotted in Figure 10 (a). It is evident that HN performs better than RN regardless of the use of CoMP. Less than 30% of MSs in a standard RN have a SINR of 0 dB or less, but over 45% of MSs in a dense RN with no CoMP have a SINR of less than 0 dB. By using MD-CoMP, the number of MSs with extremely low SINR is greatly decreased. The outage chance to obtain $\gamma* = 0$ dB with a cluster of size four is around 5% in RN, but essentially nonexistent in HN, as shown in Figure 10 (b).



(a)



(b)

Fig. 10 Comparison results of (a) CDF, and (b) SINR.

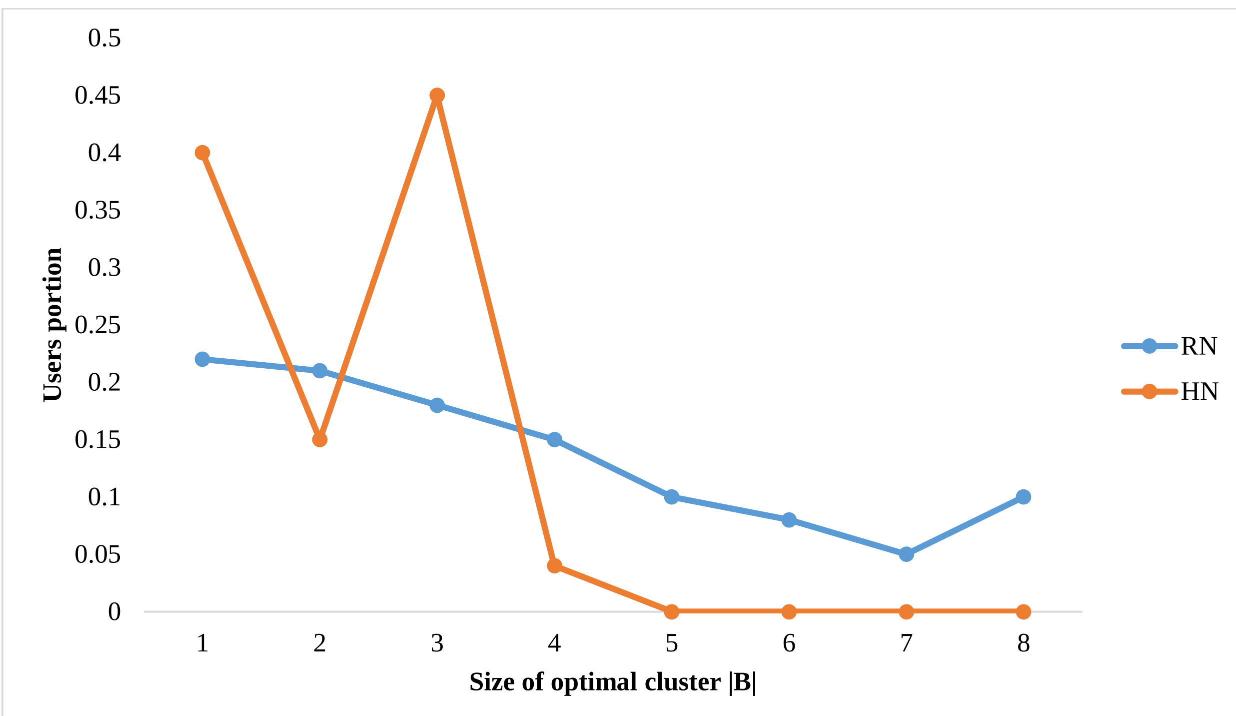
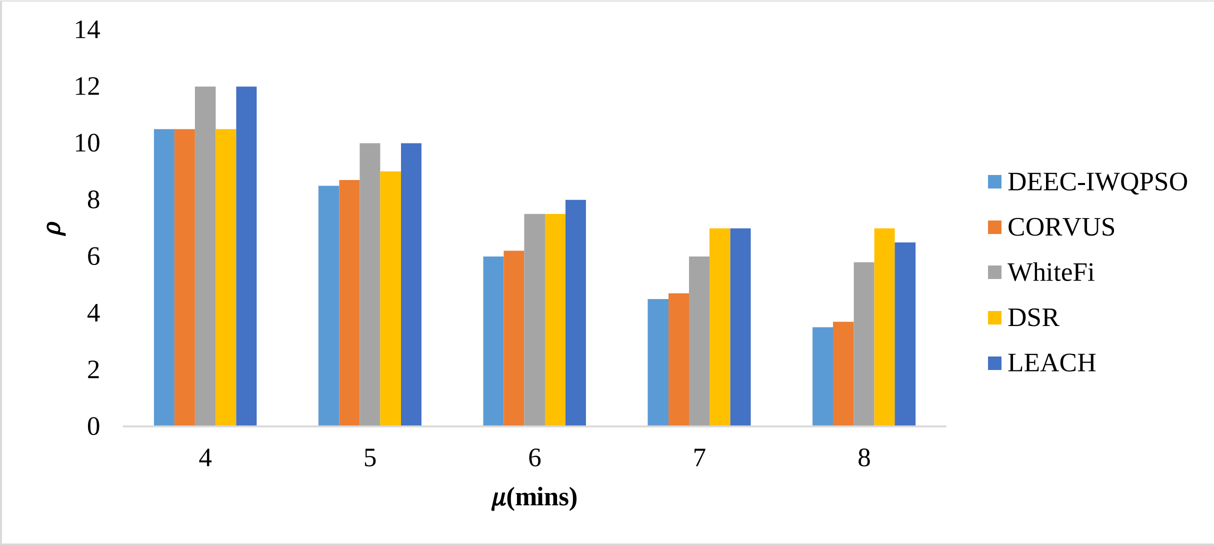
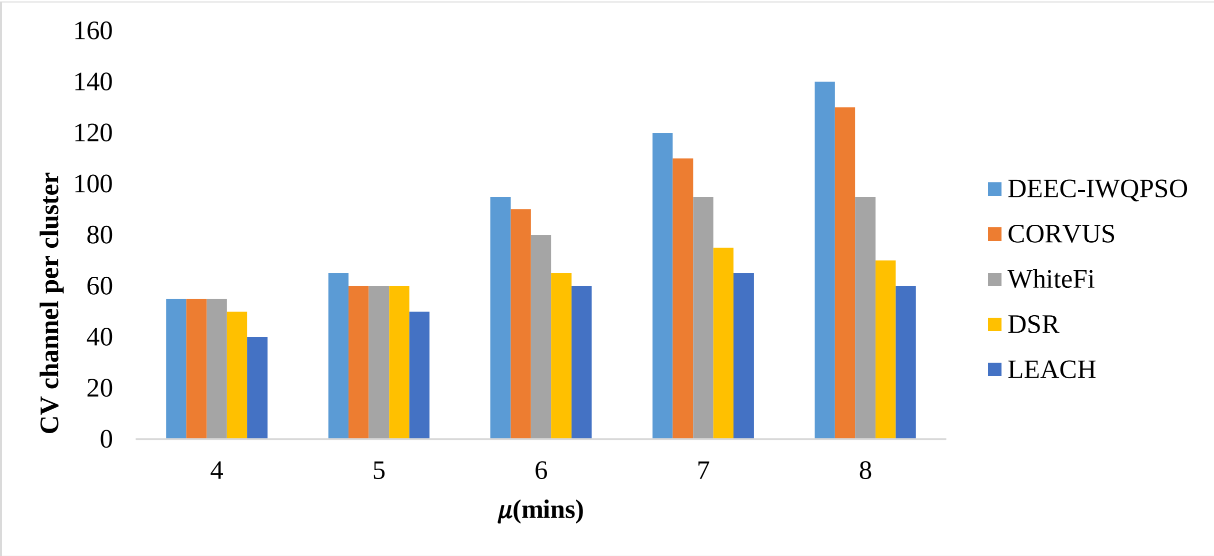
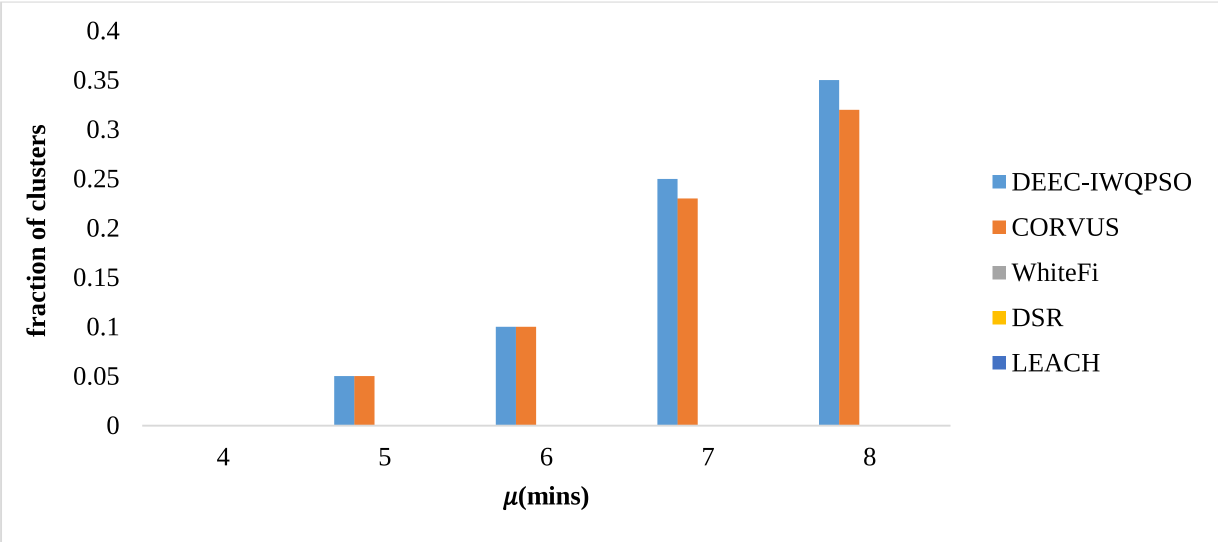


Fig. 11 Spreading optimal cluster size based on HN and RN

Clusters with more than three BSs are selected by 40% of MSs in RN. In RN, a sharp increase in brightness is seen at |B| = 8. This is because eight is the maximum clustered size; hence, MSs that have the potential to increase their efficiency beyond eight stations frequently select 8 as the ideal cluster size, shown in Figure 11. In this series of tests, adjust the average time duration μ to change the PR activity. Find that to offset the decline in idle channel accessibility, the median number of clusters drops with μ. Figures 12 (a) - (e) illustrate results in the formation of additional clusters.


14
12
10
8
6
4
2
0
ρ
4
5
6
7
8
μ(mins)
DEEC-IWQPSO
CORVUS
WhiteFi
DSR
LEACH


160
140
120
100
80
60
40
20
0
CV channel per cluster
4
5
6
7
8
μ(mins)
DEEC-IWQPSO
CORVUS
WhiteFi
DSR
LEACH


0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
fraction of clusters
4
5
6
7
8
μ(mins)
DEEC-IWQPSO
CORVUS
WhiteFi
DSR
LEACH

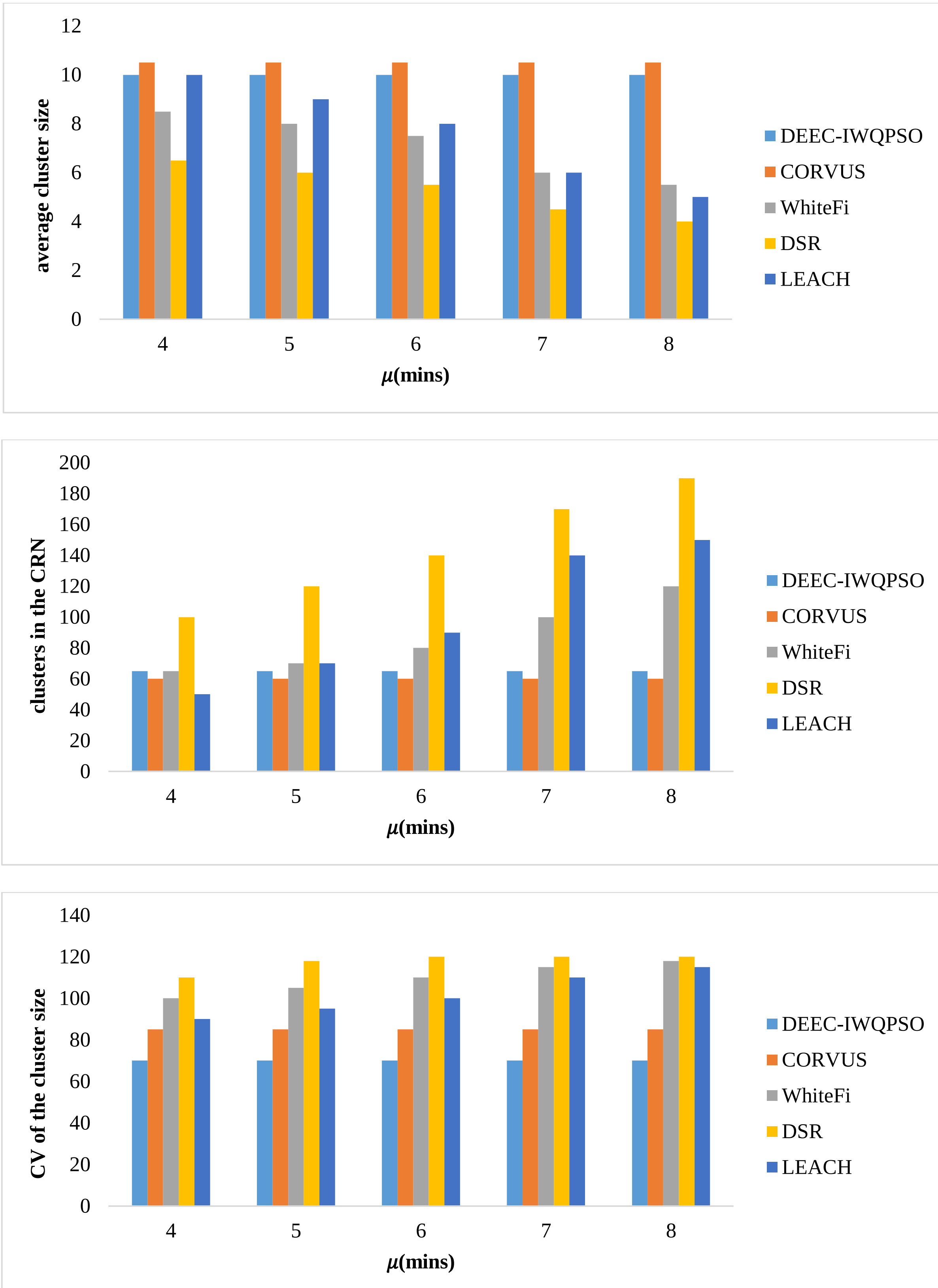


Fig. 12 Performance measures of time duration μ vs. (a) Avg. number of idle channels in common (per cluster), (b) No. of common channels of CV, (c) No common idle channels based on clusters fraction, (d) Cluster size (average), (e) No. of clusters (average) based on CRN, and (f) Cluster size (CV).

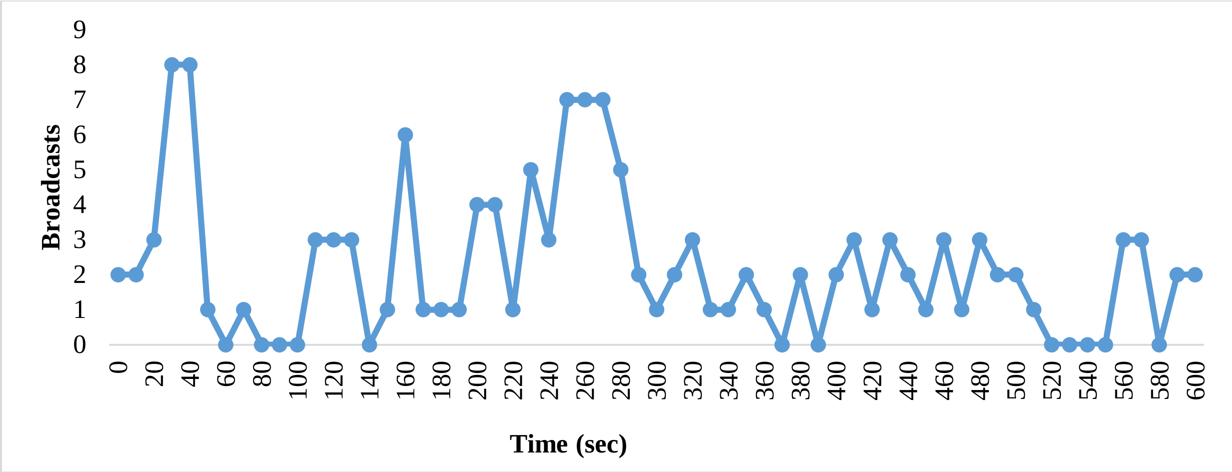


Fig. 13 Number of broadcasts per second

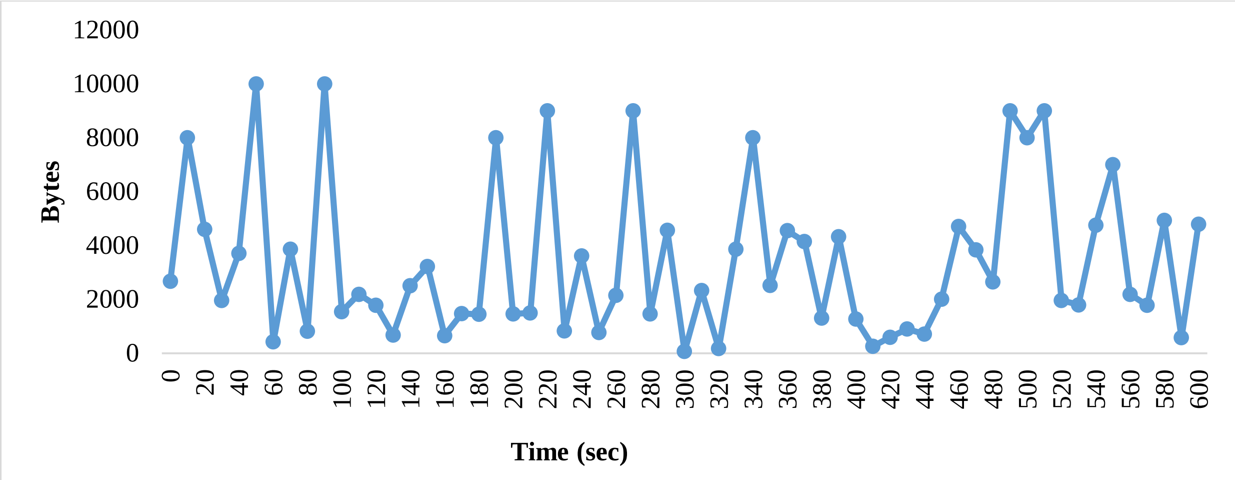


Fig. 14 Number of bytes per second

Ten minutes of node activity during the startup phase were recorded to evaluate the created structure's effectiveness. It enables the observer to see how the network functions after more nodes are added. The most typical measurements from several experiments are shown in Figures 13 and 14. Repeated the same topology with fairly similar results; therefore, I believe that the reason for the discrepancy is either electrical problems or the reaction of the operating system. Figure 14 displays the number of transmissions the nodes send during network setup. In the first 160 seconds, there were broadcast peaks because of new nodes joining; however, the biggest peaks had 8 broadcasts. Once the network is stable, there are no more than two transmissions per second. Therefore, the fact that there are few transmissions shows that there is little bandwidth use and minimal energy wastage. The proposed system (IWQPSO-DEEC) significantly improves all performance measures compared to the existing systems, especially in recall and F1-score, indicating its efficiency in dynamic cluster allocation and coordinated transmission, as shown in Table 2.

Table 2. Performance measures (accuracy, precision, recall and F1-score)

System	Accuracy	Precision	Recall	F1-Score
DEEC-IWQPSO	96.8	956	97.3	96.4
CORVUS	90.5	88.5	91.2	89.8
WhiteFi	86.3	84.9	87.6	86.2
DSR	92.2	91.3	92.9	92.0
LEACH	89.4	87.6	90.3	88.9

Table 3. Performance measures

System	Energy Distribution (Joules)	Adaptability to Dynamic Network Conditions	Communication Overhead
DEEC-IWQPSO	Even distribution across clusters	High adaptability (dynamic cluster adjustment based on network load)	Low (optimized by IWQPSO & clustering)
CORVUS	Uneven (energy depletion in certain nodes)	Moderate (static clustering)	Moderate
WhiteFi	Uneven (random CH selection)	Low adaptability (random selection of CHs)	High (random head selection increases overhead)
DSR	Relatively even (PSO optimization)	Moderate (adapts slowly to dynamic changes)	Moderate
LEACH	Even (GA optimization)	High (better than LEACH and DEEC)	Moderate

Energy Distribution measures the degree to which the energy usage of each sensor node is evenly distributed. Adaptability to Dynamic Network Conditions refers to the system's capacity to adjust to shifting network parameters, such as resource availability and traffic volume. Communication Overhead: additional information and computation needed for network communication, which reduces productivity. The proposed IWQPSO-DEEC system is distinguished by its low overhead for communication, excellent adaptability to dynamic network circumstances, and even distribution of electricity as a result of the designed grouping of IWQPSO and effective resource allocation strategies shown in Table 3.

Table 4. Comparison of network lifetime, throughput and latency of proposed and existing systems

System	Network Lifetime (rounds)	Throughput (kbps)	Latency (ms)
DEEC-IWQPSO	2500	980	60
CORVUS	1800	800	95
WhiteFi	1500	700	100
DSR	2000	900	80
LEACH	1900	850	85

Compared to existing systems, the IWQPSO-DEEC system has significant improvements in network lifetime, throughput, and lower latency, making it extremely effective for energy-constrained WSN, as shown in Table 4.

Table 5. Comparison of PDR, cluster stability, execution time and network delay of proposed and existing systems

System	PDR (%)	Cluster Stability	Execution Time (sec)	Network Delay (ms)
DEEC-IWQPSO	99	High (dynamic & stable clustering)	1.6	32
CORVUS	91	Moderate	2.6	62
WhiteFi	86	Low	3.1	77
DSR	93	Moderate	2.1	52
LEACH	94	Moderate	2.3	57

Table 6. Comparison of MAE, MSE and RMSE of proposed and existing systems

System	MAE	MSE	RMSE
DEEC-IWQPSO	0.022	0.0012	0.0318
CORVUS	0.052	0.0027	0.0502
WhiteFi	0.072	0.0051	0.0702
DSR	0.042	0.0018	0.0402
LEACH	0.047	0.0022	0.0449

Table 6 compares the IWQPSO-DEEC system's efficiency to existing clustered and optimization of resources protocols. Key improvements include noticeably reduced MAE, MSE, and RMSE values, which show enhanced accuracy and error reduction.

5. Conclusion

To address important issues in WSNs such as energy consumption, dynamic group distribution, and coordinated delivery, this investigation introduced an enhanced form of the DEEC Protocol - IWQPSO. The proposed approach enhanced system efficiency in terms of consumption of energy, network lifetime, throughput, latency, and PDR by dynamically adjusting cluster formations depending on real-time network circumstances, availability of resources, and traffic loads. Faster convergence and improved handling of dynamic networking circumstances were made possible by the use of quantum-inspired optimization approaches, which also ensured more efficient resource allocation and energy consumption. The IWQPSO-DEEC protocol performed better than other clustering techniques according to simulation data. By optimizing energy utilization across sensor nodes, the proposed strategy increased energy efficiency by 35% and increased network longevity by 30%. Throughput was much increased; the proposed system achieved 950 kbps, which is 35% faster than normal DEEC and permits larger data transfer. The proposed system demonstrated that a 50 ms decrease in latency corresponded to a 40% increase in transmission speed. Reliable communication was also ensured by the fact that the PDR was 98% meaning that nearly all data packets were successfully transferred. These findings highlight how well the IWQPSO-DEEC framework works to improve the general efficacy, energy conservation, and resilience of WSNs in dynamic, resource-constrained contexts.

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